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Solar radiation prediction using Artificial Neural Network techniques: A review

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ABSTRACT

Solar radiation data plays an important role in solar energy research. These data are not available for location of interest due to absence of a meteorological station. Therefore, the solar radiation has to be predicted accurately for these locations using various solar radiation estimation models. The main objective of this study is to review Artificial Neural Network (ANN) based techniques in order to identify suitable methods available in the literature for solar radiation prediction and to identify research gaps. The study shows that Artificial Neural Network techniques predict solar radiation more accurately in comparison to conventional methods. The prediction accuracy of ANN models is found to be dependent on input parameter combinations, training algorithm and architecture configurations. Further research areas in ANN technique based methodologies are also identified in the present study.

Contents

1. Introduction

The solar radiation is an important parameter for solar energy research but is not available for most of the sites due to nonavailability of solar radiation measuring equipment at the meteorological stations. Therefore, it is essential to predict solar radiation for a location using several climatic variables. These variables are sunshine duration, maximum ambient temperature, relative humidity, latitude, longitude, day of the year, daily clear sky global radiation, total cloud cover, temperature, clearness index, altitude, months, average temperature, average cloudiness, average wind velocity, atmospheric pressure, reference clearness index, mean diffuse radiation, mean beam radiation, month, extraterrestrial radiation, evaporation and soil temperature. The sunshine duration is easily available and measured at most of the sites so it is generally used for modeling of solar radiation [1,2]. The information about solar radiation, solar energy system models, site specific data and publications, is given in the inventory prepared by Myers for NREL [3]. Several authors have developed empirical models for solar radiation prediction [4–15]. The prediction is found to be accurate with quality measured data [16,17]. It is evaluated with mean absolute percentage error (MAPE) i.e. MAPE $\leq$ 10% means high prediction accuracy, 10% $\leq$ MAPE $\leq$ 20% means good prediction, 20% $\leq$ MAPE $\leq$ 50% means reasonable prediction, MAPE $\geq$ 50% means

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Nomenclature

BP	back propagation
LM	Levenberg–Marquardt
MAPE	mean absolute percentage error
MBE	mean bias error
R	correlation coefficient
R^2	absolute fraction of variance
RMSE	root mean square error

inaccurate forecasting [18]. The main objective of this study is to review Artificial Neural Network (ANN) based techniques in order to identify suitable methods available in the literature and to identify research gaps.

This paper is organized as follows: ANN based solar radiation prediction models developed by various researchers for different sites, are described in Section 2.1. The selection of relevant input parameters to ANN models for prediction is presented in Section 2.4. The comparison of different solar radiation prediction models is shown in Section 3. The research gaps in solar radiation prediction are identified in Section 4. Finally, the conclusions are given in Section 5.

2. Artificial Neural Network techniques for solar radiation prediction

ANN is a section in artificial intelligence (AI) which works as a superb tool for exploration as it is competent to solve non-linear function estimation, data sorting, pattern detection, optimization, clustering and simulation. These are called 'black-box' modeling procedures to carry out non-linear mapping. Its design primarily involves input layer, hidden layer, output layer, connection weight and biases, activation function and summation node. Its action is divided into two stages: learning (training) and generalization (recalling). In training network weights and biases are used to generate the target output by reducing the error function. The networks are progressed through learning algorithm and trained by epochs which are entire cycle of all training data existing in the network. The learning techniques are divided into supervised, unsupervised, reinforcement and evolutionary learning. The supervised learning is based on totaling of variance between the real network output and preferred output. The weights and biases are modified by organizing training pattern set and resultant errors between the preferred output and the subsequent network output. Thus supervised learning proceeds as closed loop feedback system where error is the feedback signal. The error degree is characterized through mean squared error (MSE). The MSE is determined after each epochs and the learning process is finished when MSE is minimized.

ANN techniques have become alternative methods to conventional techniques and are used in a number of solar energy applications. Kalogirou [19] has reviewed the use of ANN in renewable energy systems applications. Mellit et al. [20] has reviewed ANN for sizing of photovoltaic systems and Mellit and Kalogirou [21] has reviewed ANN for photovoltaic applications. ANN has many applications for modeling, prediction and forecasting of monthly, daily and hourly solar radiation which are discussed in the following section.

2.1. Global solar radiation prediction

The availability of global solar radiation on the ground surface is one of the most important factors for functioning of a solar energy system. Therefore, this section deals with the application of ANN techniques in prediction of global solar radiation using different meteorological and geographical variables [22–63].

AI-Alawi and AI-Hinai [22] applied multilayer feed forward network, back propagation (BP) training algorithm to predict global radiation for Seeb locations. It is found that using location, month, mean pressure, mean temperature, mean vapor pressure, mean relative humidity, mean wind speed and mean sunshine hours as inputs, give mean MAPE range from 5.43 to 7.30. Sözen et al. [23,24] developed ANN model for estimation of solar radiation in Turkey using meteorological and geographical data as input variables. The learning algorithm for network is scaled conjugate gradient, Pola-Ribiere conjugate gradient, Levenberg–Marquardt and a logistic sigmoid transfer function. The MAPE value for the MLP network is found to be 6.73%.

Mohandes et al. [25] used ANN for modeling of global solar radiation in Saudi Arabia as a function of latitude, longitude, altitude and sunshine duration. The BP algorithm is used for training the different configuration of multi-layer feed-forward neural networks. It is found that the network consisting of 4, 10, 1 neurons in input, hidden, output layers perform best and MAPE varies from 6.5 to 19.1 in testing stations.

Ouammi et al. [26] developed ANN model for estimating monthly solar irradiation of 41 Moroccan sites. The data period used is from 1998 to 2010 and inputs for the networks are normalized values of longitude, latitude and elevation. The predicted solar irradiation varies from 5030 to 6230 W h/m^2/day.

Rehman and Mohandes [27] used four combinations of input parameters (day, maximum air temperature, mean air temperature, relative humidity) to estimate diffuse solar radiation for Abha city in Saudi Arabia. The results show that using relative humidity and daily mean temperature performs better than other combinations with mean square error (MSE) of 5.18×10^{-7}.

Lazzús et al. [28] used ANN model with wind speed, relative humidity, air temperature and soil temperature as inputs to estimate hourly global solar radiation for La Serena in Chile. It is found that R^2 is 94%, indicating strong correlation between hourly global solar radiation and meteorological data.

Azeez [29] applied feed forward back propagation Neural Network to estimate monthly average global solar irradiation on a horizontal surface for Gusau, Nigeria. The sunshine duration, maximum ambient temperature and relative humidity are taken as input parameters and solar irradiation as output parameter. The results (R=99.96, MPE=0.8512, RMSE=0.0028) have shown good agreement between the estimated and measured values of global solar irradiation.

Linares-Rodríguez et al. [30] applied ANN for predicting solar radiation in Spain based on latitude, longitude, day of the year, daily clear sky global radiation, total cloud cover, skin temperature, total column water vapor and total column ozone as inputs. The RMSE between ANN predicted and measured values are found to be 13.52% (for training stations) to 14.20% (for testing stations). The 9 year measured data from 83 metrological stations is used for model validation in Andalusia (Spain). The methodology can be used to generate daily global solar radiation for locations where meteorological information is available. The ANN estimation is found to be distance dependent and cannot be extrapolated if only a few meteorological stations are used for training or these stations do not cover the entire area of study. Therefore, for accurate prediction of solar radiation for sites located at greater

distances data from large number of stations covering the region have to be used and also the solar maps could be generated with a reasonable accuracy for the region of interest.

Koca et al. [31] developed an ANN based model for estimation of solar radiation for seven cities in Mediterranean region of Anatolia, Turkey. Six different combinations of latitude, longitude, altitude, months, average temperature, average cloudiness, average wind velocity and sunshine duration are used as input parameters to find the best ANN configuration for estimation. It is shown that the number of input parameters affects R^2 value in estimation of solar radiation.

Voyant et al. [32] studied the effect of exogenous meteorological variables in prediction of daily solar radiation. Due to exogenous variables normalized root mean square error (nRMSE) is found to be 0.5%, 1% for Corsica Island, France and addition of both endogenous, exogenous variables decreases nRMSE by 1% thus improving prediction accuracy.

Khatib et al. [33] used feed forward multilayer perception model to predict clearness index in Malaysia, using latitude, longitude, day's number and sunshine ratio as input data. The clearness index (K_T) is used to find global radiation (H) and diffuse radiation (H_D).

$$H = K_T H_o \tag{1}$$

$$H_D = (0.9505 + 0.91634K_T - 4.851K_T^2 + 3.2353K_T^3)H \tag{2}$$

The MAPE in estimating global, diffuse radiation are 7.96%, 9.8% respectively for cities of Kuala Lumpur, Alor, Setar, Johor Bahru, Kuching and Ipoh in Malaysia. The mean absolute percentage error (MAPE) measures the accuracy of estimated solar radiation value and is defined by following relation:

$$\left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{SR_{i\,(estimated)} - SR_{i\,(measured)}}{SR_{i\,(measured)}}\right|\right) \times 100 \tag{3}$$

where $SR_{i\,(estimated)}$ is estimated solar radiation, $SR_{i\,(measured)}$ is measured solar radiation and n is the number of data points.

Yadav and Chandel [34] made use of ANN fitting tool for the prediction of solar radiation at 12 Indian stations with different climatic conditions. The model incorporates input parameters as latitude, longitude, height above sea level, sunshine hours and solar radiation as output. The LM algorithm is used to train the ANN. It is found that RMSE in the ANN model varies from 0.0486 to 3.562 for Indian region.

Elminir et al. [35] proposed ANN model based on determination and pattern selection techniques to predict diffuse fraction (K_D) in hourly and daily scale. The global solar radiation and other meteorological parameters, like long-wave atmospheric emission, air temperature, relative humidity and atmospheric pressure are taken as input parameters to ANN model and K_D as output parameter. The result analysis shows that ANN based estimation technique for diffuse fraction is more suitable to predict the diffuse fraction in hourly scale than the regression model.

Hontoria et al. [36] proposed MLP model to develop solar radiation map for Spain with different climatic conditions. The MLP model utilizes days, hour order number, daily clearness index and hourly clearness index as inputs for prediction. This methodology is better than classical methods and can be used for developing a solar map.

Elminir et al. [37] used multilayer feed forward network for predicting infrared, ultraviolet, global solar radiation at Helwan, Aswan monitoring stations. The input data of network are wind direction, wind speed, ambient temperature, relative humidity, cloudiness and water vapor. The RMSE are found to be 5.02%, 7.46% and 3.97% for infrared, ultraviolet and global solar radiation respectively.

Table 1
Error evaluation and architecture of Ångström and ANN models (hyperbolic tangent activation function).

Model types	Input parameters	No. of hidden layer	Hidden layer neurons	RMSE (%)
ANN-1	TDSH, MDSH	1	77	6.28
ANN-2	M, MDSH	1	61	6.64
ANN-3	M, DT_{max}	1	61	10.15
ANN-4	M, MDSH, DT_{max}	1	46	6.11
ANN-5	M, MDSH, DT_{max}	2	23–46	6.57
ANN-6	TDSH, MDSH, DT_{max}	1	46	5.97
ANN-7	TDSH, MDSH, DT_{max}	2	23–46	5.67
AT-1	MTSH, SH, ER, DGR			13.36
AT-2	TDSH, MDSH, ER, GR			5.81
AT-3	TDSH, MDSH, ER, GR			10.4

Tymvios et al. [38] carried out a comparative study of ANN and Ångström models in estimation of solar radiation. The parameters used as inputs are theoretical daily sunshine duration (TDSH), measured daily sunshine duration (MDSH), month (M), daily maximum temperature (DT_{max}), monthly mean value of theoretical sunshine duration (MTSH), monthly mean value of measured sunshine duration (SH), extraterrestrial radiation (ER), monthly mean value of daily global radiation (DGR), total global radiation (GR), daily extraterrestrial radiation (DER). Seven different ANN models and 3 different Ångström models are developed using input parameter combinations as shown in Table 1. The maximum RMSE of ANN model is found to be 10.15 using M, DT_{max} as input parameters whereas Ångström Model gives RMSE as 13.36 using MTSH, SH, ER, DGR showing ANN model gives better results than Ångström Model.

Alam et al. [39] developed ANN model for estimating beam solar radiation by reference clearness index (RCI).The RCI is the ratio of measured beam solar radiation at normal incidence to the beam solar radiation as calculated by Hottel's clear day model. The input data to the network are latitude, longitude, altitude, month of the year, mean duration of sunshine per hour, rainfall ratio, relative humidity and reference clearness index as output. The RMSE in ANN model varies from 1.65% to 2.79% for Indian locations.

Mishra et al. [40] used radial basis functions (RBF) and five MLP networks to estimate direct solar radiation for eight stations in India. The network uses inputs as latitude, longitude, mean sunshine per hour duration, relative humidity ratio, rainfall ratio and month. It is shown that MLP performed better than RBF. The RMSE value of 7–29% is obtained for the RBF and (0.8–5.4%) for the MLP.

Jiang [41] estimated monthly mean daily diffuse solar radiation for eight cities (Haerbin, Lanzhou, Beijing, Wuhan, Kunming, Guangzhou, Wulumuqi and Lasa) in China using feed-forward back propagation neural network. The inputs for the network are monthly mean daily clearness index, sunshine percentage and output is monthly mean daily diffuse fraction. The RMSE in empirical models are 0.783, 0.781 whereas in ANN model is 0.746, showing accurate estimation of ANN than empirical models.

Mubiru and Banda [42] elaborated feed forward back-propagation ANN architecture to estimate monthly average daily global solar irradiation for Uganda locations. Inputs to the ANN model are annual average of sunshine hours, cloud cover, relative humidity, rainfall, latitude, longitude and altitude. The ANN model utilizes Levenberg–Marquardt (LM) training algorithm and MAPE,

R^2 are 0.3%, 97.4% respectively and it give better results than sunshine based conventional model.

Şenkal and Kuleli [43] used ANN and physical model to estimate solar radiation for 12 cities in Turkey. The input values to the network are latitude, longitude, altitude, month, mean diffuse radiation and mean beam radiation. The data of 9 cities are used to train a neural network and 3 cities to test the network. The RMSE values using the MLP and the physical model are 54 W/m^2 and 64 W/m^2 (training cities); 91 W/m^2 and 125 W/m^2 (testing cities), respectively. Şenkal [44] also used generalized regression neural network (GRNN) for estimating solar radiation in Turkey. The model uses latitude, longitude, altitude, surface emissivity, land surface temperature as inputs with solar radiation as output. The results show that RMSE, R^2 are 0.1630 MJ/m^2, 95.34% for training stations and for testing stations as 0.3200 MJ/m^2, 93.41% respectively.

Jiang [45] found ANN model better than empirical regression model in predicting solar radiation. Latitude, altitude and mean sunshine duration are taken as inputs and global solar radiation as output to predict solar radiation of 13 cities in China. The $R^2=0.97$, RMSE = 1.4 MJ/m^2 which show accuracy of ANN model in predicting solar radiation.

Benghanem et al. [46] developed ANN model to estimate solar radiation in Al-Madinah (Saudi Arabia). The data for 4 years are used to train a neural network and 1 year data for testing, validation of the network. The inputs are different combination of air temperature, relative humidity, sunshine duration and the day of year. The correlation coefficient of 97.65% is obtained using sunshine duration and air temperature as inputs to the ANN model. In addition sunshine duration gives more accurate results.

Fadare [47] used neural toolbox to built multilayered feed-forward back-propagation neural networks with different architecture for prediction of solar energy potential over 195 cities in Nigeria. Geographical and meteorological data of 195 cities in Nigeria for period of 10 years (1983–1993) from the NASA geo-satellite database are used for training, testing the network. The graphical user interface (GUI) is developed for assessment of solar energy potential in Nigeria. The R^2 for training and testing datasets are higher than 90% suggesting high reliability of model for evaluation of solar radiation.

Azadeh et al. [48] considered location, month, mean value of maximum temperature, minimum temperature, relative humidity, vapor pressure, total precipitation, wind speed and sunshine hours as most effective input parameters to various ANN models. The input parameters are selected using correlations with global radiation, resulting in elimination of location and month. The ANN model with lowest MAPE is selected for prediction of global radiation. The proposed method for estimation is integrated ANN–MLP model. In this model regression analysis is performed to find out relevant input parameters. The data is divided into training and testing part. The MLP models are developed with different hidden layers, neurons, training algorithm. The MLP model with least MAPE is utilized for prediction of solar radiation. The results show that MAPE is 0.03 using back propagation, momentum, weight decay, pruning as learning methods. In addition the compared results of ANN models and Ångström model proving ANN models are better in estimation than Angström model.

Sözen and Arcaklioğlu [49] predicted solar-energy potential in Turkey using ANN. Scaled conjugate gradient, pola-ribiere conjugate gradient, LM learning algorithm and logistic transfer function are used in ANN model. The geographical coordinates, mean sunshine duration, mean temperature and month are taken as input parameters and solar radiation as output parameter. According to the authors, the best value of R^2 are 99.55%, 99.98% for Siirt, Artvin in Turkey respectively. The MAPE is less than 3.832% therefore the predicted solar resource values are very close to the actual values for all the months.

Rahimikhoob [50] used an ANN for estimation of global solar radiation (GSR) in semi-arid environment for Ahwaz (Iran).The GSR is estimated as a function of air maximum and minimum air temperature, extraterrestrial radiation as shown in Fig. 1. The multilayer feed forward network with one input, hidden and output layer are used for training using BP algorithm. The datasets consist of training, testing and validation. The transfer function is log sigmoid and neurons in hidden layer are determined empirically by changing the neurons from 3 to 11. The results (RMSE 2.534 MJ/m^2/day, R^2 88.9%) are obtained for 6 neurons in hidden layer showing ANN is capable of estimating GSR from temperature, extraterrestrial radiation and are found better than Hargreaves and Samani [51] equation.

Hasni et al. [52] modeled global solar radiation using air temperature, relative humidity as inputs in south-western region of Algeria. The training is done using LM feed-forward back propagation algorithm and transfer function in hidden, output layers is hyperbolic tangent sigmoid, purelin respectively. The MAPE, R^2 are 2.9971%, 99.99%.

Lu et al. [53] built ANN model for estimating daily global solar radiation over China using Multi-functional Transport Satellite (MTSAT) data. The model utilizes daytime mean air mass, surface altitude as different input combinations and daily clearness index as output. The results show that the ANN model which uses daytime mean air mass, surface altitude inputs result in better correlation value to model than the model which incorporates only surface altitude as input.

Yildiz et al. [54] used two models (ANN-1, ANN-2) for the estimation of solar radiation in Turkey. The ANN-1 model uses latitude, longitude, altitude; month and meteorological land surface temperature as inputs whereas ANN-2 model utilizes latitude, longitude, altitude, month and satellite land surface temperature as inputs. The R^2 for ANN-1, ANN-2 are 80.41%,

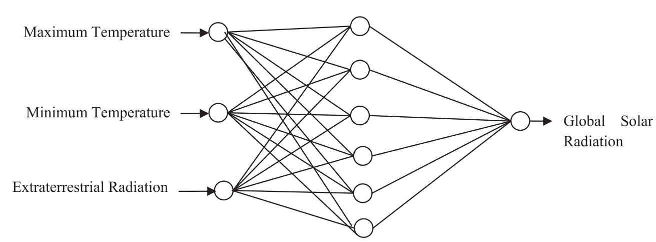


Fig. 1. ANN model to predict global solar radiation.

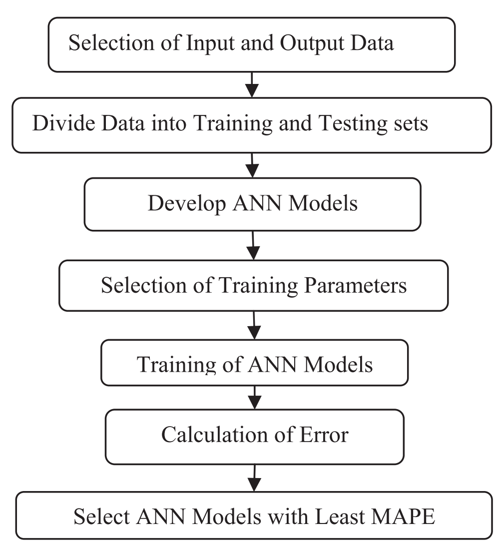


Fig. 2. ANN prediction methodology.

82.37% respectively for testing station showing better estimation of ANN-2 model than ANN-1 model.

Rumbayan et al. [55] used ANN to estimate the monthly solar irradiation for Indonesia. The model utilize NASA measured data and 9 inputs variables i.e. average temperature, average relative humidity, average sunshine duration, average wind speed, average precipitation, longitude, latitude, latitude and month of the year. The ANN prediction methodology is shown in Fig. 2. The MAPE is found to be 3.4% with 9 neurons in hidden layer. The GIS technology for solar mapping is shown for 30 provinces in Indonesia.

Rehman and Mohandes [56] used RBF network approach for modeling of diffuse and direct normal solar radiation for sites in Saudi Arabia based on input data: day, global solar radiation, ambient temperature and relative humidity. The result indicates that RBF (50 hidden neurons, 0.1 spread constant) predicts direct normal solar radiation with MAPE of 0.016 and 0.41 for diffuse solar radiation.

Şenkal et al. [57] used generalized regression neural networks (GRNNs) for estimating solar radiation from latitude, longitude, altitude, month and meteorological satellite data (mean land surface temperature) for sites in Turkey. The RMSE values range from 0.0144% to 4.91%.

Sumithira and Kumar [58] used neuro-fuzzy inference system (ANFIS) for monthly global solar radiation prediction (MGSR) in Tamilnadu, India. The ANFIS model incorporates ambient temperature, relative humidity, atmospheric pressure and wind speed as input parameters and solar radiation as output. The R value in ANFIS model is 98.98%.

Rahoma et al. [59] developed ANFIS neuro-fuzzy system to predict the solar radiation in Helwan, Egypt (NARIG) using 10 years (1991–2000) daily solar radiation data. The result shows that Takagi-Sugeno (TS) fuzzy model provides good accuracy of 96% and RMSE lower than 6%.

Iqdour and Zeroual [60] used Takagi–Sugeno (TS) fuzzy systems to model daily global solar radiation in Marrakesh (Morocco). The RMSE value of 0.76 is obtained for training phase and 0.82 for validation phase. In addition, a comparison between the results obtained by the TS fuzzy system, lost solar component, clearness index models show the effectiveness of TS fuzzy system for the prediction of daily global solar radiation. Şen et al. [61] developed a geno-fuzzy model to assess solar potential for three stations in Turkey. The developed model is compared with Angström [62], Şahin and Şen [63] showing its high accuracy with RMSE variation from 0.041 to 0.053.

Wang et al. [64] developed wavelet neural network (WNN) model based on temperature, clearness index, and phase space reconstruction radiation data. The results indicate that using phase space reconstruction data of solar radiation to WNN is less time-consuming and improves the prediction accuracy.

2.1.1. Prediction of solar radiation on tilted surfaces

In this section we discuss solar radiation prediction models for tilted surfaces. The prediction of solar radiation on tilted surface requires optimum tilt angle determination for solar panels for specific sites. Yadav and Chandel have discussed various optimum angle determination techniques in detail [65]. The nonlinear relationship between the tilt angle and the amount of solar radiation incident on the solar collector makes the calculation of optimum tilt angle and radiation difficult to estimate as such ANN techniques can be used [66–70]. Mehleri et al. [66] used tilt angle and orientation as inputs to radial basis function neural network (RBFNN) for predicting solar radiation on inclined surface. Fuzzy algorithm is used for training RBFNN and R^2 is found to be 99.99%. In another study Mehleri et al. [67] used RBFNN as a function of horizontal surface solar radiation, extraterrestrial radiation, solar zenith angle and solar incidence angle on a tilted plane for estimation of solar radiation on inclined surfaces in Athens. The R^2 is found 96%, proving accurate estimation by the model. Notton et al. [68] developed three ANN models based on declination angle, hour, zenith angle, hourly extraterrestrial horizontal irradiation, hourly global irradiation for estimating hourly global irradiation on 45°, 60° tilted planes for Mediterranean site of Ajaccio, France. The first and second ANN models estimate hourly global irradiation on 45°, 60° tilted plane respectively whereas third ANN model estimates for both tilt angles 45° and 60°. The R^2 of first, second and third ANN models are 99.79%, 99.82% and 99.70% respectively. Celik and Muneer [69] used generalized regression neural networks (GRNN) to predict solar radiation on tilted surface in Iskenderun, Turkey. The GRNN utilizes input parameters as global solar irradiation on horizontal surface, declination and hour angles. The R^2, MAPE are found to be 98.7%, 14.9 W h/m^2 respectively.

Chatterjee and Keyhani [70] used 14 inputs (latitude, ground reflectivity and 12 month irradiance values) to estimate total solar radiation (SR) on tilted surface by ANN as shown in Fig. 3. The output layer contains five neurons corresponding to four quarterly optimum tilt angles and total solar radiation on tilted surface. The activation function in hidden layer is hyperbolic tangent and in output layer it is linear. The LM algorithm is used for training. The number of hidden layers and its neurons are selected randomly. The RMSE becomes small during training and best validation performance is 3.2033 at epoch 7. The ANN estimates optimum tilt angle with 3° accuracy and can also be used for estimating optimum tilt angles online.

2.2. Daily solar radiation prediction

The daily solar radiation (DSR) is one of the most important parameters in solar energy applications especially for sizing of

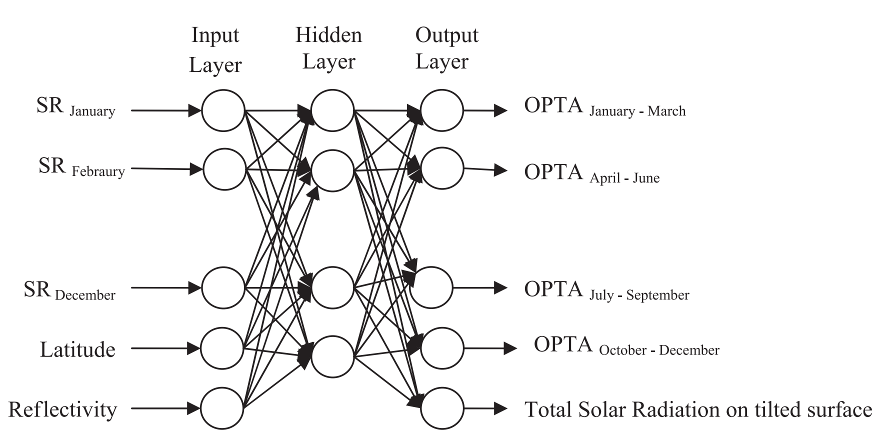


Fig. 3. ANN architecture to predict solar radiation on tilted surface.

standalone solar photovoltaic (PV) systems. The inaccuracy and lack of measured DSR data leads to high cost of a PV system. The DSR prediction has been given by a number of researchers [71,72,75–86].

Bulut and Büyükalaca [71] have used trigonometric function for estimating the daily global radiation at 68 locations in Turkey. This model has day of the year as one independent parameter. Solar radiation data of 10 years are used for training and testing the model. The estimations are in good agreement with both the measured data and the data available in the literature.

Elminir et al. [72] estimated hourly and daily values of the diffuse fraction (K_D) using ANN in Egypt. The network incorporates inputs as the global solar radiation, long-wave atmospheric emission, air temperature, relative humidity and atmospheric pressure to predict hourly K_D. For daily K_D, ANN has three inputs i.e. daily value of the global radiation, extraterrestrial irradiation and sunshine fraction. The standard error (SE) in estimating hourly K_D using ANN in Erbs [73] model are 4.2%, 5.6% respectively. The Gopinathan and Soler [74] model estimates daily K_D with SE range 4.84–17.76% while in ANN model SE varies from 2.51% to 5.96% showing better accuracy of ANN model.

Moustris et al. [75] used MLP based on hourly data of air temperature, relative humidity, sunshine duration, clouds octals and latitude to create missing mean, maximum and minimum global and diffuse solar irradiance hourly data for Greek locations. The correlation coefficient values are statistically significant at 99% confidence level ($\rho < 0.01$). Thus, hourly global and diffuse mean hourly solar irradiance values predicted by ANN are in good agreement with actual measurements.

Mellit et al. [76] proposed adaptive α model for predicting hourly global, diffuse and direct solar irradiance in Saudi Arabia. The correlation coefficient (R) value for validation data set is greater than 97.0% and the mean bias error (MBE) is less than 0.8. The best R values of 96.65% and 94.94% are obtained by using sunshine duration and air temperature as input parameters to ANN model. In other study, Mellit et al. [77] also proposed a hybrid model (ANN–MTM) i.e. combination of multi-layer perceptron (MLP) and library of Markov transition matrices (MTM) to generate sequence of daily global solar radiation data for Algeria. The ANN model incorporates feed forward network and back propagation learning algorithm. In ANN–MTM hybrid model first block acts as ANN model for the generation of monthly average global solar irradiation data $\overline{H}$ from the geographical coordinates (latitude, longitude and altitude) of the site. The second block consist of Markov transition matrices (MTM) to generate daily clearness indexes K_T values from the monthly clearness indexes $\overline{K}_T$ obtained by the first block, and clearness index data are divided by the corresponding extraterrestrial values H_o to obtain daily global solar radiation data H. The proposed model is compared with the traditional models and correlation coefficient ranging from 90% to 92% is obtained.

Behrang et al. [78] used Multi-layer perceptron (MLP) and radial basis function (RBF) neural networks for modeling of daily GSR for Dezful city in Iran. The networks employ six proposed combinations of (day of the year (Day), daily mean air temperature (AT), relative humidity (RH), sunshine hours (SH), evaporation (E) and wind speed (WS)) as inputs variables and daily GSR as output shown in Fig. 4. The measured data between 2002 and 2005 are used for training the networks while the data for 214 days from 2006 are used for testing the network. The results indicate that input combination of wind speed, day of year, daily mean air temperature, relative humidity and sunshine hours in MLP network is better than the other ANN cases with MAPE and R^2 of 5.21% and 99.57%. Moreover, the input combination of daily mean air temperature, day of year and sunshine hours to RBF network had an acceptable accuracy i.e. MAPE of 6.53% and R^2 of 99.45%.

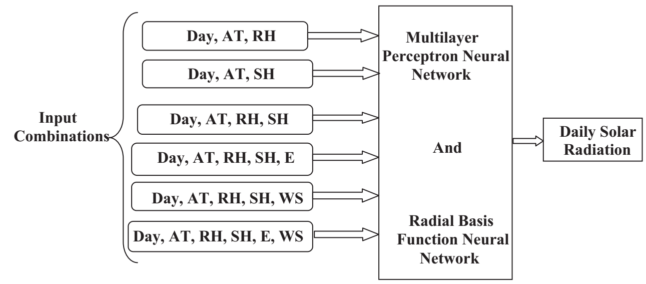


Fig. 4. Daily solar radiation prediction ANN model.

Benghanem and Mellit [79] used Radial Basis Function network (RBFN) for predicting daily global solar radiation data at Al-Madinah (Saudi Arabia). The RBFN utilizes different combinations of air temperature, sunshine duration, relative humidity and day as input parameters. The RBFN built on sunshine duration and air temperature as input parameters gives accurate results having correlation coefficient of 98.80%. The results show that RBFN predictions are more accurate than conventional regression models.

Bilgili and Ozgoren [80] applied multi-linear regression (MLR), multi-nonlinear regression (MNLR) and feed-forward Artificial Neural Network (ANN) methods for modeling daily total global solar radiation in Adana city of Turkey. The measured sunshine duration, air temperature, wind speed and date of the year (monthly and daily) are used as independent variables to the MLR, MNLR and ANN models. The developed methods have been applied and tested in Adana city of Turkey with. MAPE 9.23% and R^2 97.5%. Asl et al. [81] used multi-layer perceptron (MLP) neural networks to predict daily global solar radiation for Dezful city in Iran. Day of the year, daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed, soil temperature values are taken as input parameters and MAPE is found to be 6.08.

Yacef et al. [82] compared Bayesian Neural Network (BNN), classical Neural Network (NN) and empirical models for estimation of daily global solar radiation (DGSR) in Al-Madinah (Saudi Arabia). These models utilize air temperature, relative humidity, sunshine duration and extraterrestrial irradiation as input parameters. The automatic relevance determination (ARD) method has been used for the selection of relevant input parameters. The ARD approach demonstrates that sunshine is most relevant input parameter and air temperature is another one in estimation of solar radiation. It is shown that BNN gives more accurate results than NN and empirical models. The Bayesian approach offers selection of optimum number of hidden layers.

Cao et al. [83] improved prediction accuracy by combining recurrent BP network and wavelet, in Shanghai. The error (MJ/m^2 day) in daily solar radiation forecasting with and without wavelet analysis are 0.7193, 2.8168 respectively.

Paoli et al. [84] proposed pre-processing methods and incorporated MLP with sliding window technique for time series prediction of solar radiation. The results show that without pre-processing method normalized root mean square error (nRMSE) is 21% in comparison to Markov Chain, Bayes, K-NN methods and with pre-processing method nRMSE is 20% for clear sky, clearness index based ANN model in comparison to classical predictors (Markov chains), showing reduction in forecasting error.

Voyant et al. [85] used MLP (optimized by ALADIN forecast data and endogenous data) and auto-regressive moving average (ARMA) model to forecast hourly radiation for Ajaccio, Bastia, Marseille, Montepllier, Nice sites in Mediterranean area. The average normalized root mean square error (nRMSE) of sites is 1.7% and prediction accuracy is improved by average nRMSE gain

of 0.7%, using input as ALADIN forecast data to MLP model. The nRMSE of hybrid (ANN and ARMA) model is 14.9% whereas with ANN it is 18.4% showing decrease in prediction error.

2.3. Short term solar radiation prediction

An ANN-based forecasting of 24 h ahead solar irradiance is developed by Mellit and Pavan [86] for Trieste in Italy. The MLP consists of one input, hidden and output layer. The mean daily solar irradiance, the mean daily air temperature and the day of the month (i.e. at the time t) are given to input layer while the output layer gives 24 h of solar irradiance at the next day (i.e. at the time $t+1$). Solar irradiance and air temperature data (from July 1st 2008 to May 23rd 2009 and from November 23rd 2009 to January 24th 2010) spread over Trieste in Italy are used in training and testing the network. The K-fold cross-validation technique is used for the validation of MLP-forecaster. The correlation coefficient between predicted and measured solar irradiance is more than 98% for sunny days and is less than 95% for cloudy days.

Wanga et al. [87] used back propagation (BP) neural network for short-term solar irradiance prediction. The BP neural network with different hidden layer neurons is designed and best one is selected. The network uses solar irradiance data of 24 h and sampling interval of 1 h for prediction. The simulation results show that the double hidden layers contain 18, 13 hidden neurons and R^2 is 0.9912.

Capizzi et al. [88] investigated novel approach of wavelet recurrent neural networks (WRNNs) to forecast solar radiation at University of Catania, Italy. WRNNs are used to find out correlation of solar radiation with time scaled variation of wind speed, humidity and temperature. The WRNN is executed in wavelet domain and complete inverse wavelet transform for the prediction of output signal. This method has fast convergence, low forecasting error in comparison with hybrid neural network method and avoids calculation of inverse wavelet transform.

2.4. Selection of relevant parameters for solar radiation prediction

Prediction of solar radiation requires geographical and meteorological variables as input parameters to ANN models. Therefore, researcher has to choose most relevant parameters which give less prediction error. Several authors have identified relevant parameters for prediction [89–96].

Rehmana and Mohandes [89] used 3 combinations of easily available parameters i.e. day of the year, air temperature and relative humidity as inputs in ANN to estimate global solar radiation for Abha city in Saudi Arabia. The results show that MAPE of 4.49 is obtained using relative humidity, daily mean temperature as input parameters to ANN. In other case MAPE is 11.8 when ANN incorporates day of the year, mean temperature as input combinations while MAPE is 10.3 when maximum temperature is used instead of mean temperature.

Alam et al. [90] used ANN to estimate monthly mean hourly and daily diffuse solar radiation for Indian stations (Jodhpur, Kolkata, New Delhi, Pune, Chennai, Port Blair, Ahmedabad, Nagpur, Mumbai and Vishakhapatnam) using data from Indian Meteorological Department. The latitude (lat), longitude (long), altitude (alt), time, months of the year (moy), air temperature (at), relative humidity (rh), rainfall (rf), wind speed (ws) and net long wavelength (lw) are considered as input parameters to feed forward back propagation network (FFBPN). For finding out accuracy of prediction, different input configurations are developed as shown in Table 2. TRAINLM algorithm is used for training the model. The training data consist of 3 parts indicating different seasons i.e. summer (February–March), rainy (June–September) and winter (October–January). The FFBPN uses hidden layer neurons as 13, 11 and 9 for summer, rainy and winter season respectively. The MSE in ANN models are 10^{-5} in Type xii (for summer), 10^{-4} in Type ix (for rainy), 10^{-5} in Type xv (for winter) and maximum RMSE is 8.8% in ANN model. The results show that ANN model predicts hourly, daily diffuse radiation with better accuracy than empirical models.

Table 2
Different sets of input parameters for ANN models.

Model types	Combination of input parameters to ANN models
i	lat, long, alt, time, moy, at
ii	lat, long, alt, time, moy, rh
iii	lat, long, alt, time, moy, rf
iv	lat, long, alt, time, moy, ws
v	lat, long, alt, time, moy, lw
vi	lat, long, alt, time, moy, at, rh
vii	lat, long, alt, time, moy, at, rh, rf
viii	lat, long, alt, time, moy, at, rh, rf, ws
ix	lat, long, alt, time, at, rh, ws, lw
x	lat, long, alt, time, rh, ws, lw
xi	lat, long, alt, time, at, rf, ws, lw
xii	lat, long, alt, time, at, rh, ws, lw
xiii	lat, long, alt, time, at, rh, rf, lw
xiv	lat, long, alt, time, at, rh, ws, lw
xv	lat, long, alt, time, at, rh, lw
xvi	lat, long, alt, time, at, lw

The direct solar irradiance (DSI) data of high quality is rarely measured and it is estimated using decomposition models which calculate DSI from global solar irradiance on a horizontal surface. For estimation of DSI the development of regression models between nonlinear variables clearness index K_T and direct solar transmittance kb (direct normal irradiance/extraterrestrial irradiance) is complex. To model DSI, López et al. [91] used automatic relevance determination (ARD) method to find relevant input parameters. The ARD method proves that clearness index and relative air mass are more relevant input variables to the neural network for estimating hourly direct solar irradiance. Therefore, ARD method can be applied to locations with limited amount of measurements. Bosch et al. [92] also used ARD methodology to select inputs to ANN model for estimation of daily global irradiation on stations located in complex terrains. The forward selection pruning method is used for identifying relevant variables for prediction [93,94]. The hyper parameters associated with longitude, latitude are large showing irrelevance of these parameters as inputs and for altitude, slope, azimuth angle, day of year, daily extraterrestrial solar radiation and clearness index these are small indicating their relevance as input parameters. The ARD methodology shows that site altitude is most important parameter for solar radiation estimation over a complex terrain. The RMSE is found to be 6.0%.

Will et al. [95] used Niching Genetic Algorithms (NGA) to select most significant input parameters for estimation of solar radiation in El Colmenar (Tucumán, Argentina). The NGA involves a number of steps: codification of problem, assigning limit to each variable, finding out distance function in the search space, crossover operators, application ratios of crossover operators, initial population size and number of generations. The data from 14 stations spread in North of Argentina are used as input. The results show that NGA estimates climatic variables from data base containing missing data. The RMSE, R^2 are 2.36 MJ/m^2, 0.926 for 70 individuals/85 generations and for 200 individuals/150 generations RMSE, R^2 are 2.34 MJ/m^2, 0.928 respectively. This algorithm can be used to analyze more number of data at the same time and is useful in selecting relevant stations and variables for solar radiation estimation.

3. Comparison of different solar radiation prediction models

In this section the prediction accuracy comparison of different models is presented. Khatib et al. [96] developed linear, nonlinear,

Table 3
Global solar radiation prediction by different models.

Model	MAPE	Highlights
Linear	8.13	Easy to implement but gives more error
Nonlinear	6.93	Prediction model is developed as a nonlinear function of meteorological and geographical variables and gives less error than linear model
Fuzzy	6.71	Can be used for solving uncertainties in solar radiation estimation; better prediction accuracy than linear and nonlinear models
ANN	5.38	Due to its computational and generalization capability it has more prediction accuracy than linear, nonlinear and fuzzy model

Table 4
Least MAPE by different ANN models for the prediction of solar radiation.

Type of solar radiation predicted	ANN type and algorithm	Input parameters	Period of solar radiation data required	Prediction error
Global solar radiation on horizontal surface	Multilayer perceptron neural network training algorithm (LM feed-forward back propagation algorithms) and transfer function (hyperbolic tangent sigmoid, purelin)	Air temperature, relative humidity	Training 4 months Testing 1 month.	MAPE 2.9971 R^2 99.99%
Diffuse solar radiation	Radial basis function neural network with 50 hidden neurons and 0.1 spread constant	Day, global solar radiation, ambient temperature,relative humidity	Training 3 years Testing 1 year	MAPE 0.41
Direct normal solar radiation	Radial basis function neural network with 50 hidden neurons and 0.1 spread constant	Day, global solar radiation, ambient temperature, relative humidity	Training 3 years Testing 1 year	MAPE 0.016
Daily solar radiation	MLP neural network	Wind speed, day of year, daily mean air temperature, relative humidity, sunshine hours	Training 3 years Testing 1 year	MAPE 5.21% R^2 99.57%
Two day Forecasting of solar radiation	Wavelet recurrent neural networks	Wind speed, temperature, relative humidity	1.5 year data	RMSE < 1%

fuzzy logic and ANN models for estimation of global and diffuse radiation of five sites in Malaysia. The latitude, longitude, day number and sunshine duration are taken as input parameters. The MAPE of different models for prediction of global radiation are shown in Table 3. The MAPE values for linear, nonlinear and ANN models for the diffuse radiation are 4.35, 3.74 and 1.53 respectively showing better accuracy of estimation by ANN than other models.

Different ANN models i.e. adaptive neuro fuzzy inference system (ANFIS), Elman recurrent network (ELM), feed forward neural network (FFNN) and radial basis function (RBF) neural network are used for prediction of hourly solar radiation [97]. LM and BP algorithms are used for training all models and it is found that LM algorithm gives better result due to learning rate and gives least error between predicted and measured solar radiation. Bhardwaj et al. [98] proposed pattern similarity based clustering algorithm for estimation of daily solar radiation. The model utilized fifteen different combination of input parameters i.e. day, sunshine hour, ambient temperature, relative humidity, wind speed and atmospheric pressure from meteorological station at Solar Energy Centre, Gurgaon, India.

The Hidden Markov Model (HMM) along with Pearson *R* model is used for cluster extraction from input parameters and Generalized Fuzzy Model (GFM) is used for estimation. The maximum MAPE for all input combinations in proposed algorithm, ANFIS and ANN are found as 13.7278, 14.4956 and 21.2041 respectively. The MAPE value of 3.0083 is obtained by proposed algorithm and most relevant input parameters for solar radiation prediction are found to be sunshine hour followed by temperature, relative humidity, atmospheric pressure and wind speed. Based on the literature review of different ANN types, input parameters, solar radiation data period, learning algorithms which give least prediction error for prediction of solar radiation are shown in Table 4.

The training and testing data of minimum 3 years and 1 year respectively have been found to predict solar radiation accurately.

4. Identified research gaps in solar radiation prediction

The research gaps as identified in the present study for follow up research are as follows:

(1) In literature authors have used one, two, three, or more years of solar radiation data as available to build ANN models, and the training and testing data of minimum 3 years and 1 year respectively have been found to predict solar radiation accurately. However, further comparative analysis on this aspect can be under taken.
(2) The neurons in ANN hidden layer are changed one by one and MAPE are evaluated which is time consuming. Therefore, suitable methods should be developed to find out hidden layer neurons at which prediction error is minimum.
(3) Comparison of different ANN models such as MLP, RBF, Generalized Regression Neural Network, etc in prediction of solar radiation has to be done, in order to identify the best ANN prediction models.
(4) ANN models should be trained with optimization techniques like Particle Swarm optimization, genetic algorithm; simulated annealing techniques etc and comparative study can be performed.
(5) The effect of each variable such as sunshine duration, maximum ambient temperature, relative humidity, latitude, longitude, day of the year, daily clear sky global radiation, total cloud cover, temperature, clearness index, altitude, months, average temperature, average cloudiness, average wind velocity, atmospheric pressure, reference clearness index, mean diffuse radiation, mean beam radiation, month, extraterrestrial radiation, evaporation, soil temperature need to be considered for solar radiation prediction accuracy.
(6) Different ANN models need to be developed using latitude, longitude, altitude, extraterrestrial radiation as input parameters and checked for accuracy. This will be useful for

those locations where no meteorological stations have been established.

(7) Comparison of Niching genetic algorithm, Automatic relevance determination methodology is to be carried out in selecting most relevant input parameters to ANN models for prediction.

(8) More studies are required for the prediction of beam, diffuse and solar radiation on tilted surfaces using ANN.

5. Conclusion

A review of solar radiation prediction using different Artificial Neural Network techniques is presented in the current study. The determination of solar radiation is essential for solar system design, power generation and solar energy research. In this context, different ANN models are used to predict solar radiation on horizontal and inclined surfaces. The ANN based prediction models discussed in this study will enable researchers and solar power plant installers to determine solar radiation data with better accuracy at places where meteorological stations are not established. The ANN models are found to predict solar radiation more accurately than Ångström model, conventional, linear, non-linear and fuzzy logic models.

The geographical and meteorological parameters such as sunshine duration, maximum ambient temperature, relative humidity, latitude, longitude, day of the year, daily clear sky global radiation, total cloud cover, temperature, clearness index, altitude, months, average temperature, average cloudiness, average wind velocity, atmospheric pressure, reference clearness index, mean diffuse radiation, mean beam radiation, month, extraterrestrial radiation, evaporation, soil temperature have been used as input variables to ANN models for solar radiation prediction. However, the sunshine hours and air temperature are found to be effective inputs for ANN models for solar radiation prediction with correlation coefficient of 97.65%. The effective input can be selected using Niching genetic algorithm and automatic relevance determination (ARD) methodology.

Multilayer perceptron, radial basis function, generalized regression, Bessian Neural Network and training algorithm: back propagation, Levenberg–Marquardt have been widely used for prediction. The MLP model with LM learning algorithm and transfer function (hyperbolic tangent sigmoid in hidden layer, purelin in output layer) provide accurate prediction with minimum error. The MAPE of different ANN models get changed with the influence of geographical, meteorological variables, training algorithm and ANN architecture configuration. Therefore, the appropriate selection of input parameters is important for predicting solar radiation with better accuracy.

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